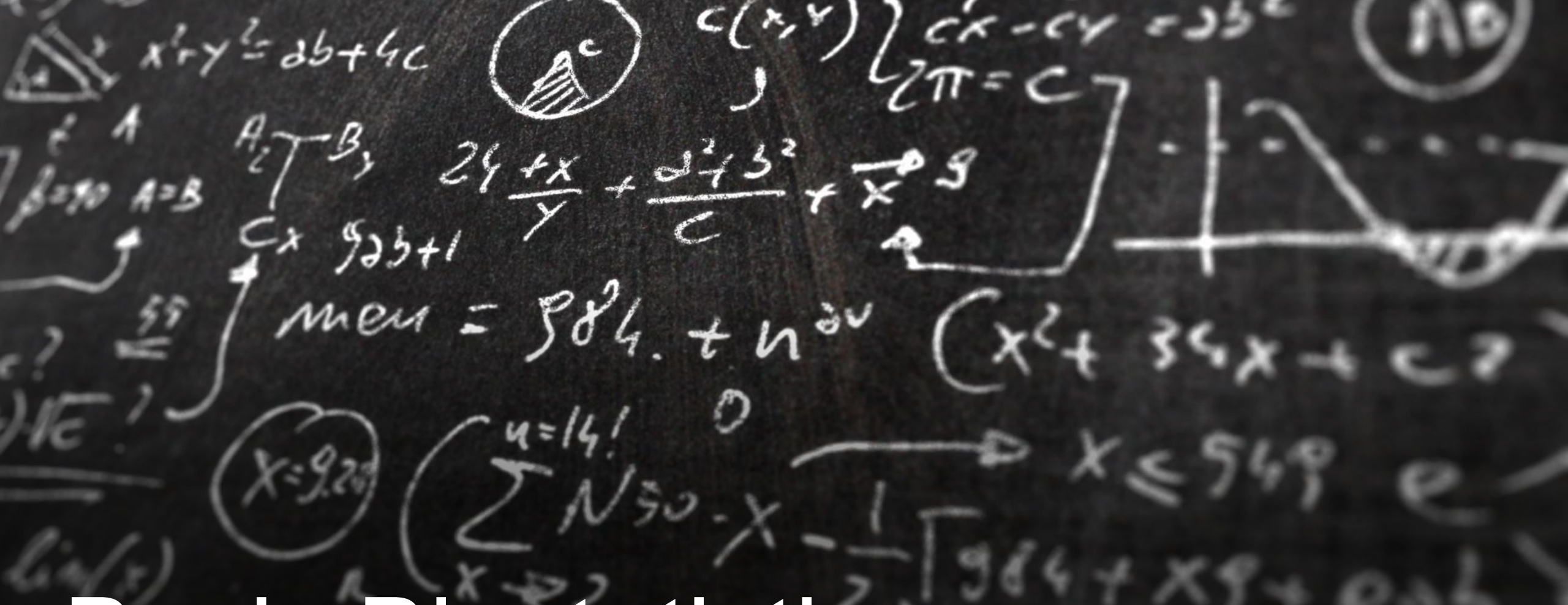

Basic Biostatistics

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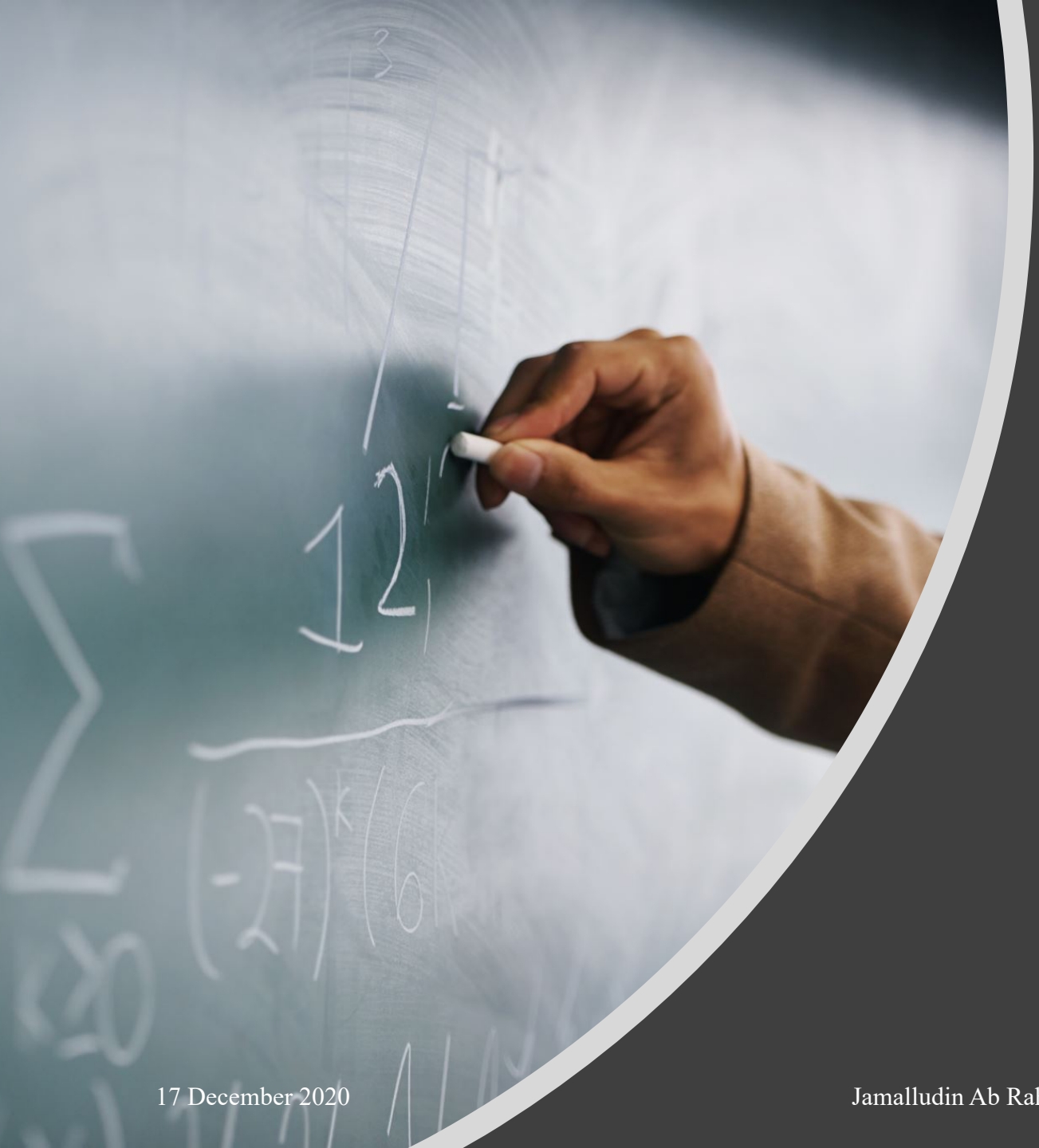
الجامعة الإسلامية العالمية ماليزيا
INTERNATIONAL ISLAMIC UNIVERSITY MALAYSIA
(Company No. 101067-P)
Garden of Knowledge and Virtue



Learning outcomes

At the end of this workshop, you should be able to

1. Describe about **population & sample**, **causality**, **level of measurement & distribution of data**
2. **Summarise** categorical & numerical data
3. Use appropriate statistical test for **bi-variable analyses**

Truth

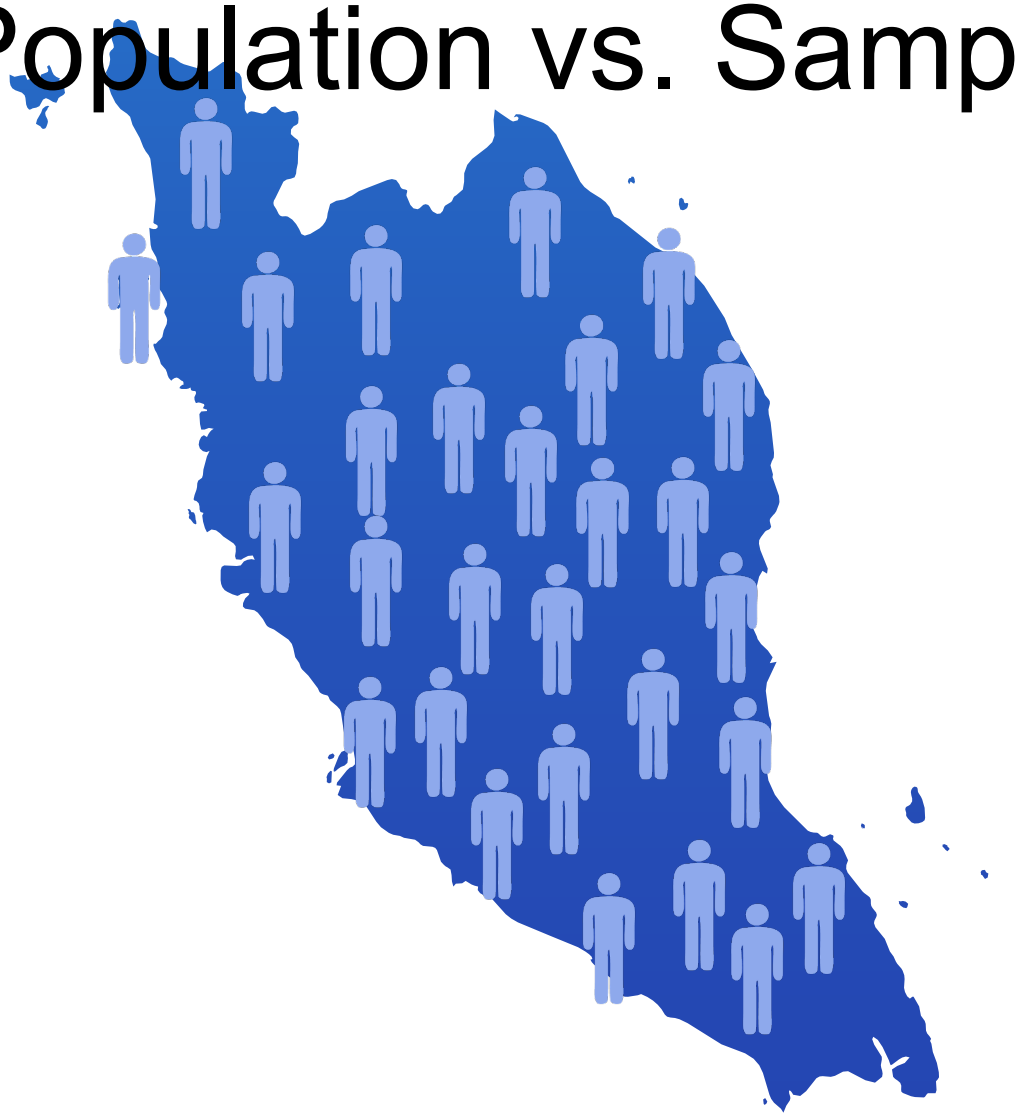
We observe.

We believe what we observe.

What we observed might not be the truth.

One of the most important objective in research is to **represent** results from **sample** analysis to the **population.**

Population vs. Sample

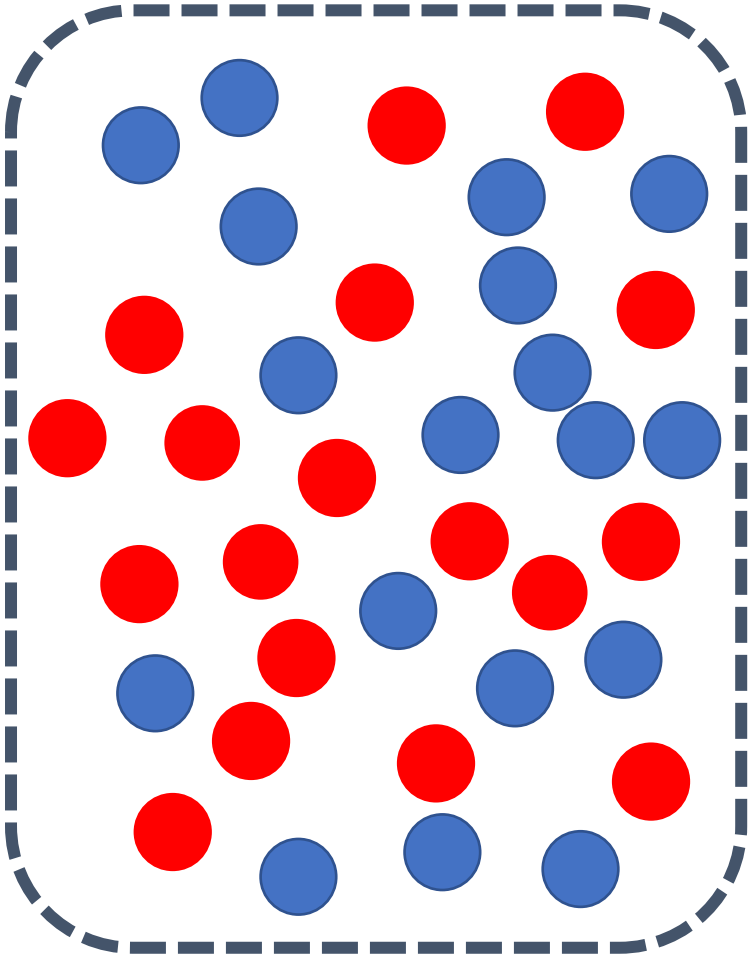


Parameter vs. Statistics

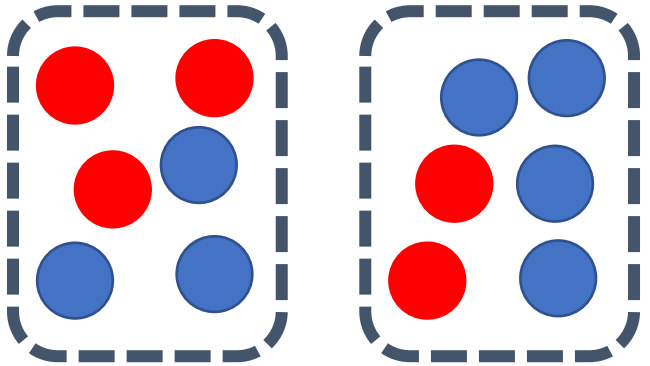
- Parameter - characteristic of the whole population
- Statistics - characteristic of a sample, presumably **measurable**.

Statistics estimate parameters

- Representative
- Sampling error
- Different samples yield different estimates
- Statistics = Parameter if sampling done properly
- How to prove?

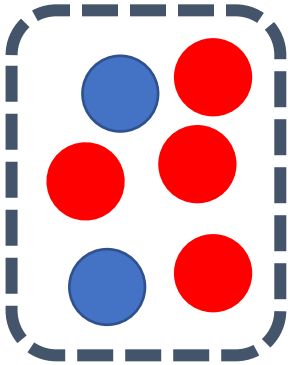


N = 35
Red = 18/35 = 51.4%
Parameter



N = 6
Red = 3/6 = 50%

N = 6
Red = 2/6 = 33.3%



N = 6
Red = 4/6 = 66.7%

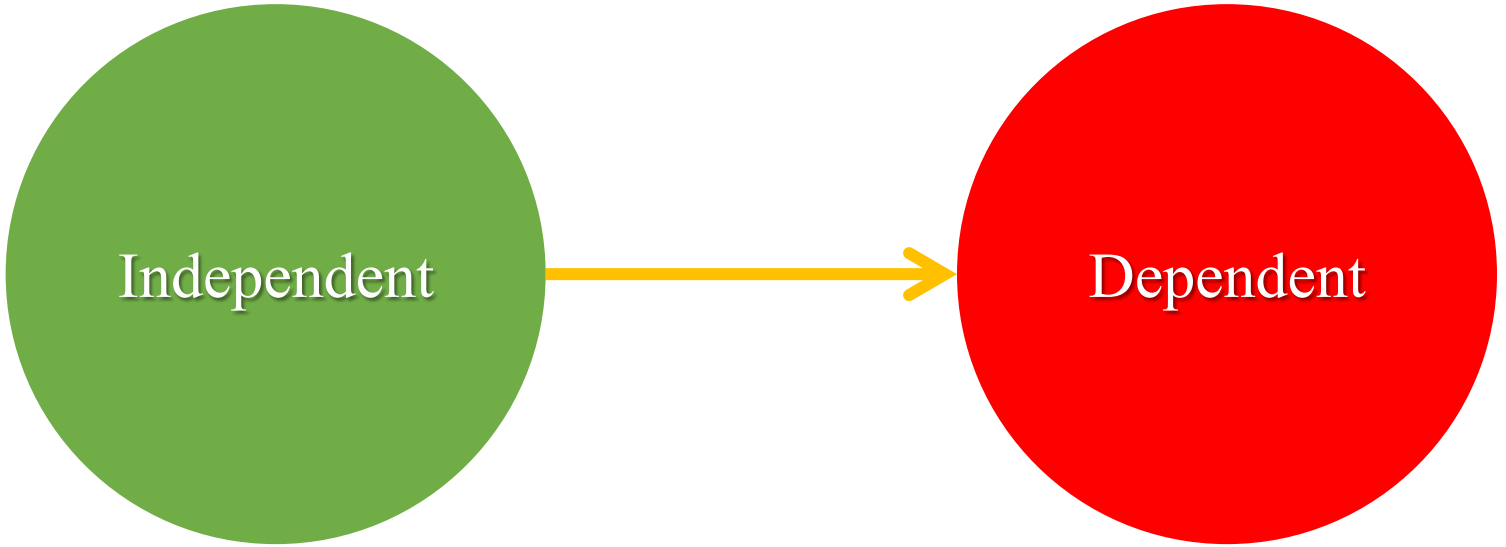
Statistics

$$\text{Average \% Red} = \frac{50\% + 33.3\% + 66.7\%}{3} = 50\%$$

Estimated
Parameter

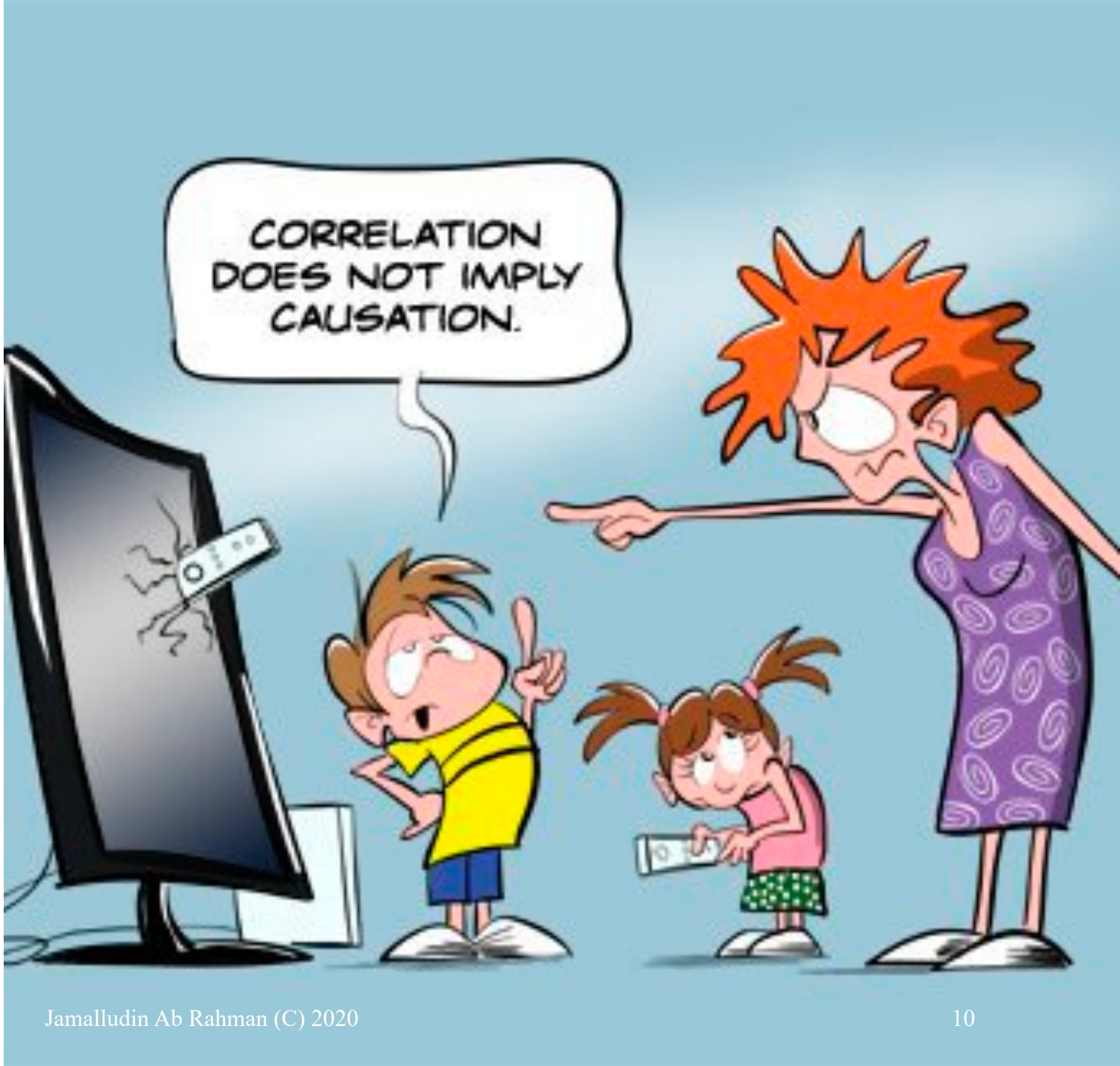
Variable & its role

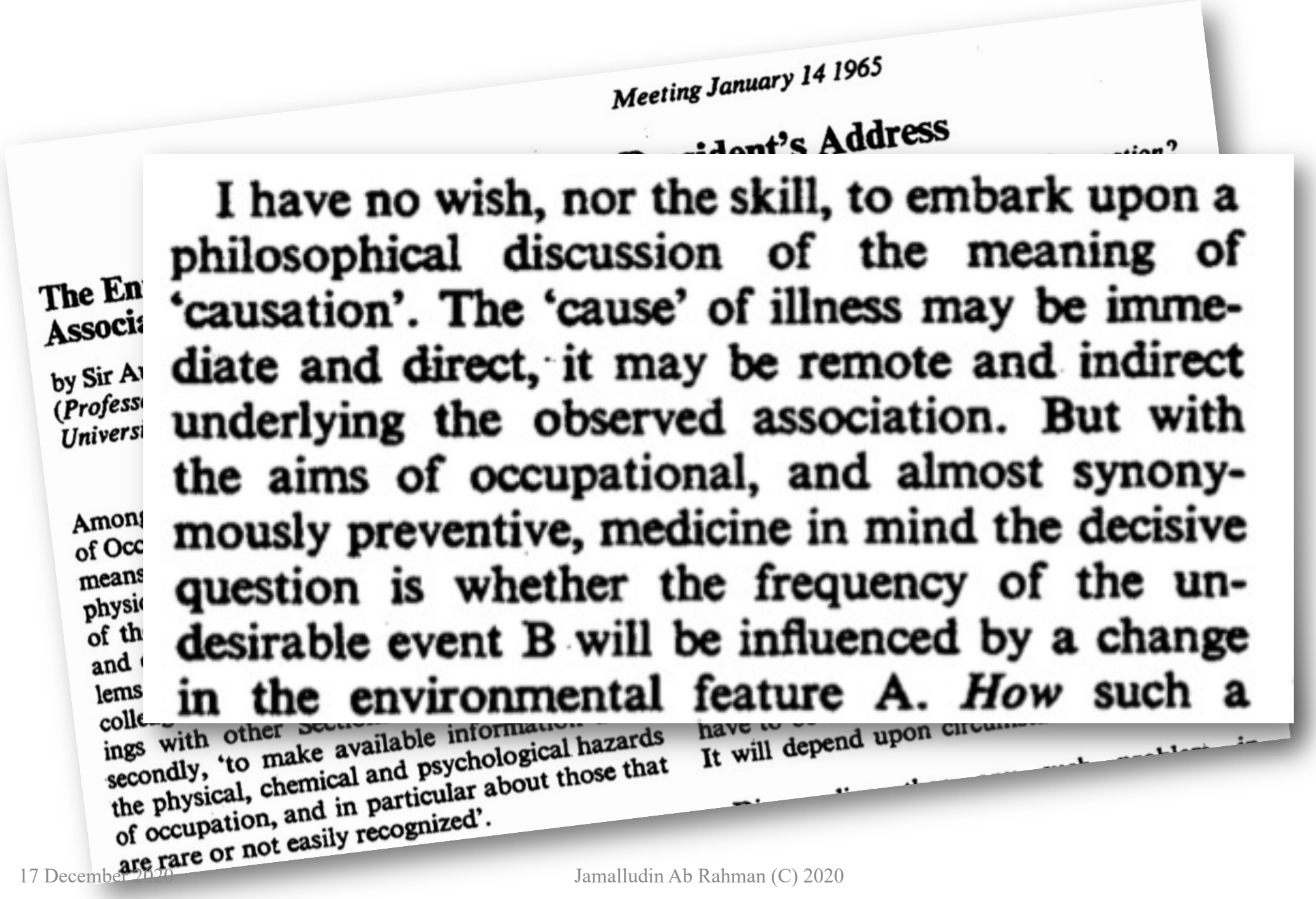
- A value and whose associated value may be changed



Causation

- Relation of events (cause and effect)
- Correlation (between two events) does not (always) imply causation
- Rooster's crow does not cause the sun to rise
- Switch does not cause the bulb to light





Meeting January 14 1965

President's Address

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by Sir A
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Among
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ings with other
secondly, 'to make available information
the physical, chemical and psychological hazards
of occupation, and in particular about those that
are rare or not easily recognized'.

have to
It will depend upon circum

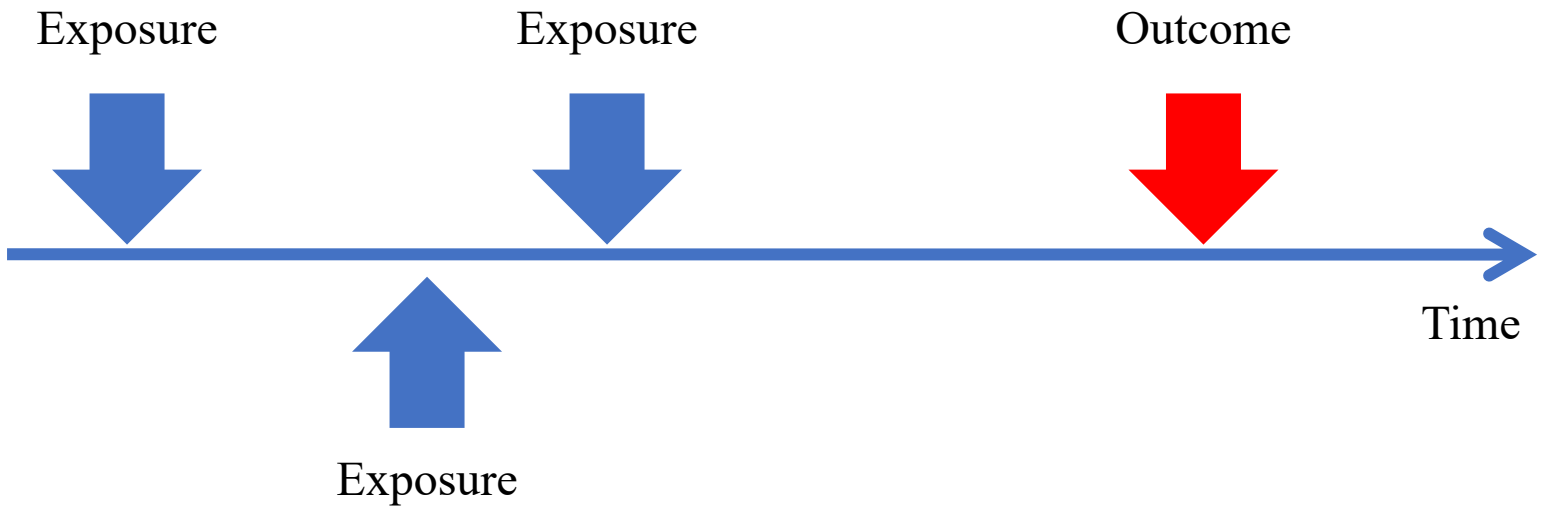
I have no wish, nor the skill, to embark upon a philosophical discussion of the meaning of 'causation'. The 'cause' of illness may be immediate and direct, it may be remote and indirect underlying the observed association. But with the aims of occupational, and almost synonymously preventive, medicine in mind the decisive question is whether the frequency of the undesirable event B will be influenced by a change in the environmental feature A. *How* such a

Hill's criteria

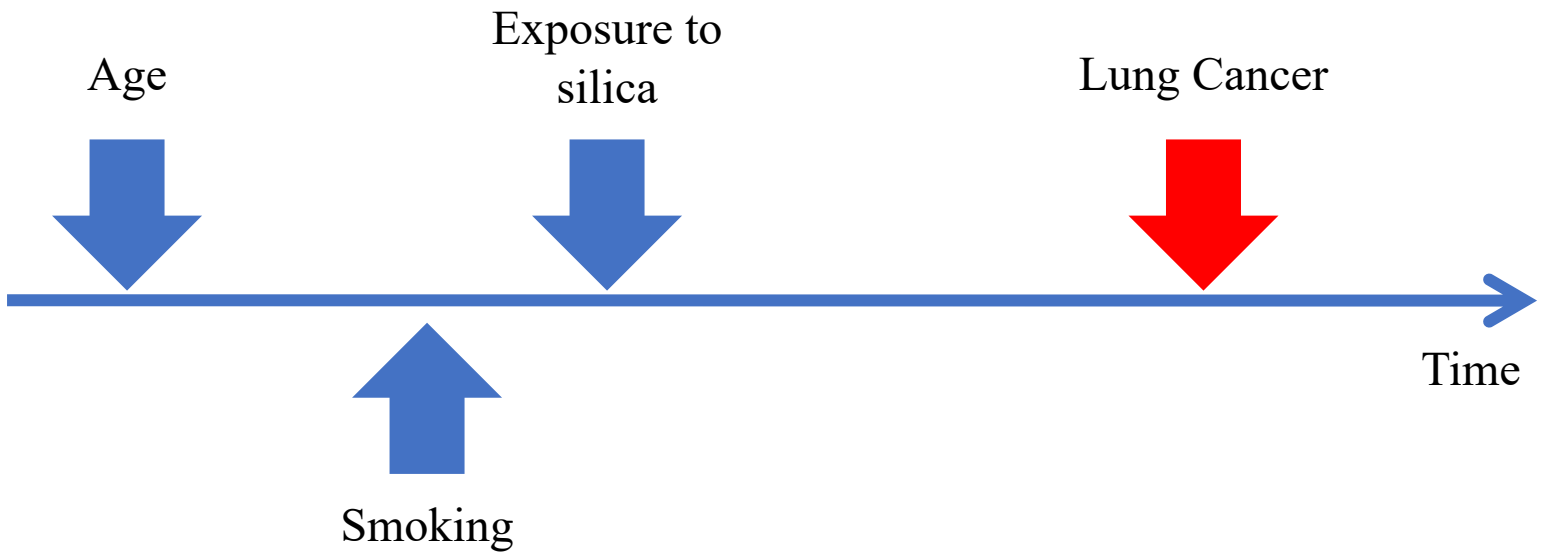
1. Strength of association
2. Consistency
3. Specificity
4. Temporality
5. Biological gradient
6. Plausibility
7. Coherence
8. Experiment
9. Analogy

Hill AB. The environment and disease: Association or causation? Proceed Roy Soc Medicine – London. 1965;58:295–300.

Time & causation



Time & causation (example)



Causal web

- Web of causation
- Conceptual framework
- Path analysis/web
- Relationship between variables
- Cause and effect

Causal webs in epidemiology

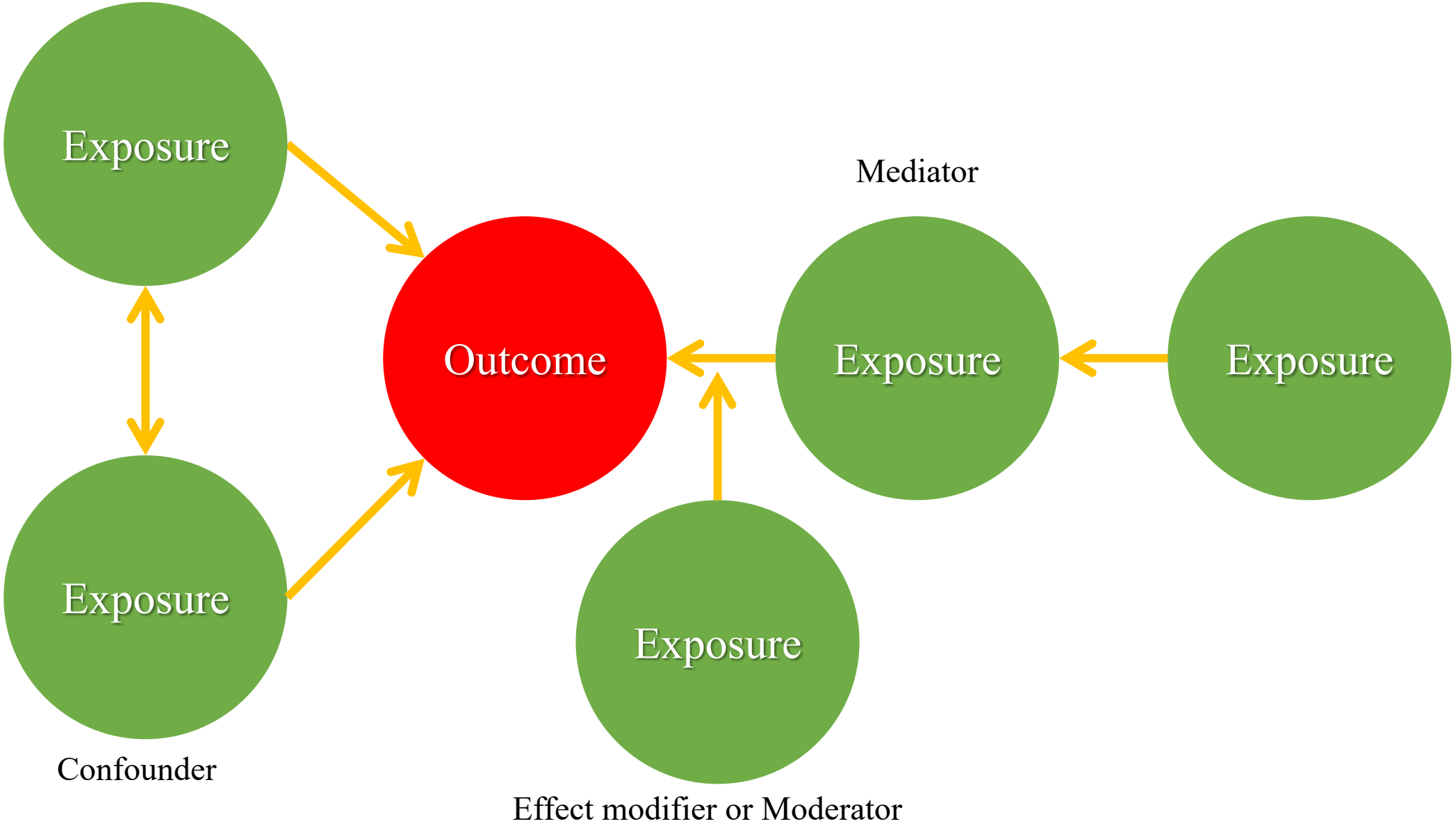
Federica Russo

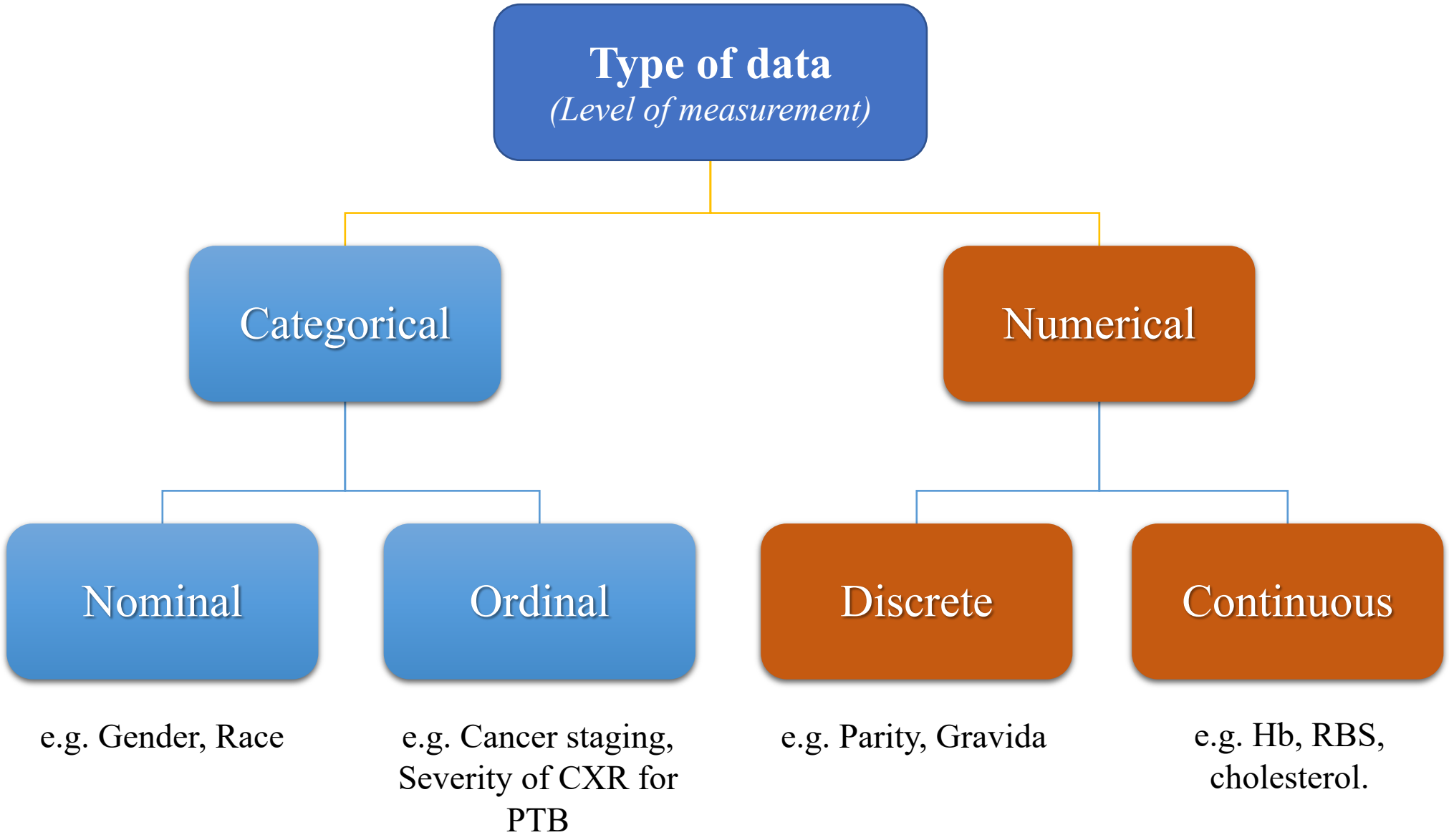
Philosophy, Kent

Draft of 30 October 2009

To appear in *Paradigmi* – Special issue on the Philosophy of Medicine.

Abstract. The notion of 'causal web' emerged in the epidemiological literature in the early Sixties and had to wait until the Nineties for a thorough critical appraisal. Famously, Nancy Krieger argued that such a notion isn't helpful unless we specify what kind of spiders create the webs. This means, according to Krieger, (i) that the role of the spiders is to provide an explanation of the yarns of the web and (ii) that the sought spiders have to be biological and social. This paper contributes to the development of the notion of causal web, elaborating on the two following points: (i) to catch the spiders we need multi-fold evidence—specifically, mechanistic and difference-making—and (ii) for the eco-social to be explanatory, the web has to be mechanistic in a sense to be specified.


Exposure
Outcome
Mediator
Exposure
Exposure
Exposure
Exposure
Confounder
Effect modifier or Moderator


Type of data
(Level of measurement)
Categorical
Numerical
Nominal
Ordinal
Discrete
Continuous
e.g. Gender, Race
e.g. Cancer staging, Severity of CXR for PTB
e.g. Parity, Gravida
e.g. Hb, RBS, cholesterol.

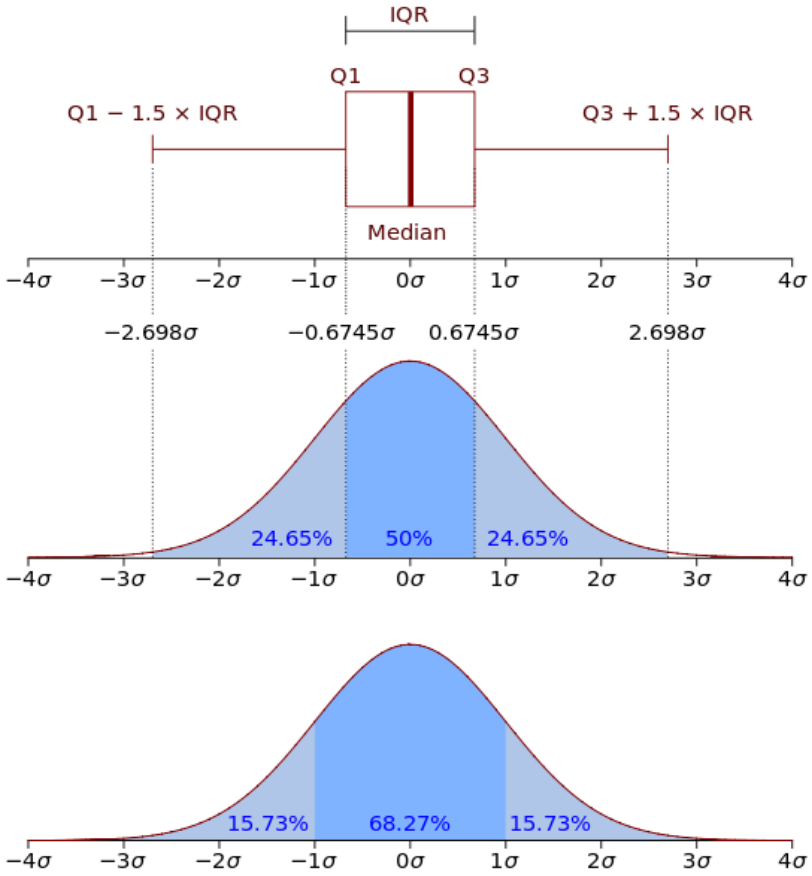
Distribution (shape) of data

- Applicable to **numerical** value
- Discrete or Continuous
- Discrete ~ *Binomial, Poisson, Negative Binomial, Hypergeometry, Multinomial etc.*
- Continuous ~ *Normal, t, chi-square, F etc.*

Knowing about the distribution means knowing the probability.

Knowing the probability will assists in reasoning.

Normal Distribution



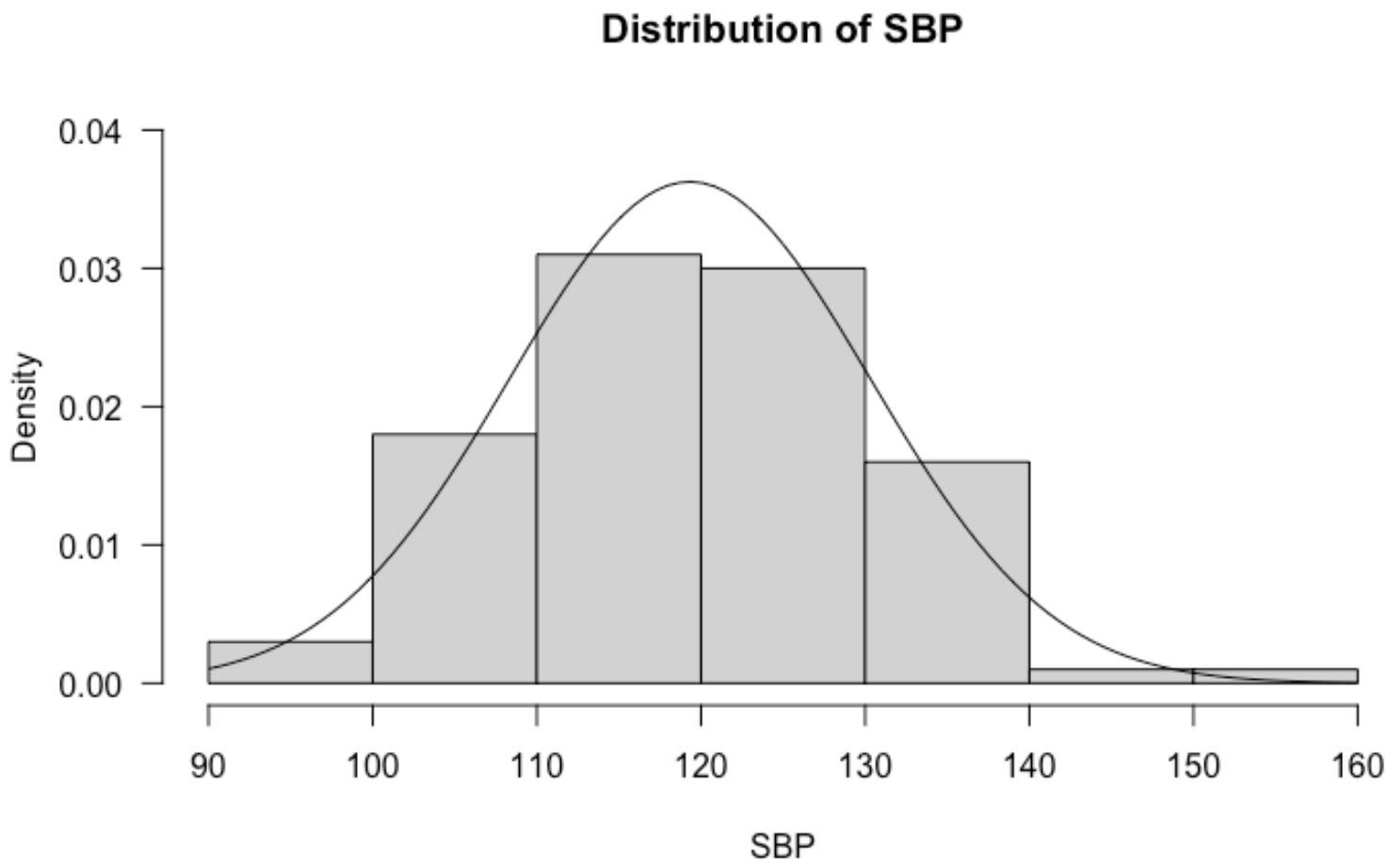
$$f(x;\mu,\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2})$$

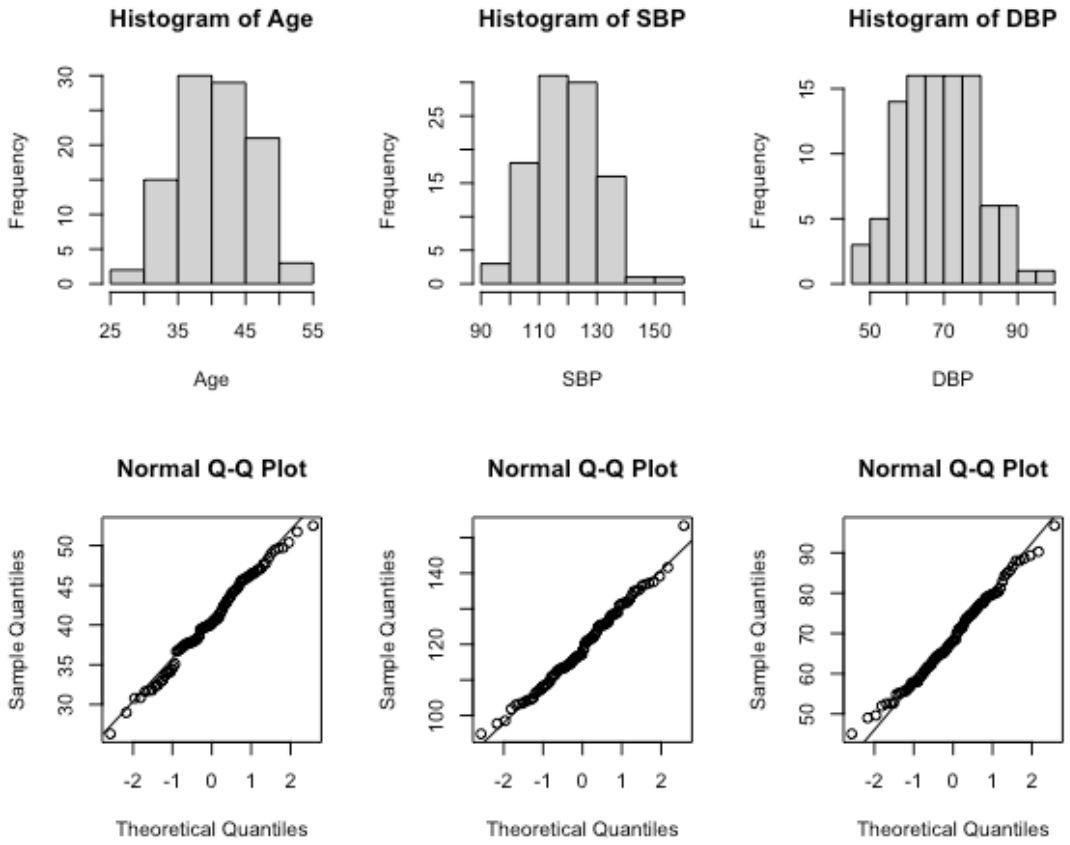
Why Normal?

- Because many biological & psychological variables are distributed normally
- Many predictive models assume Normal distribution

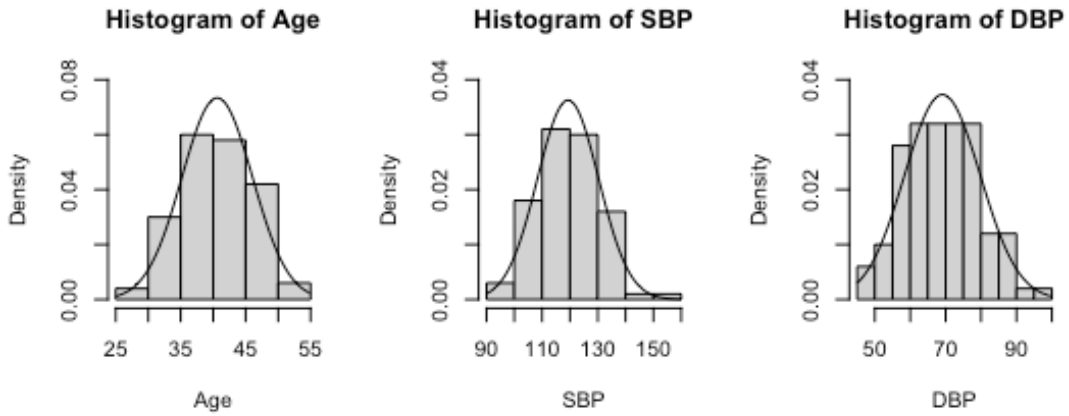
Characteristics

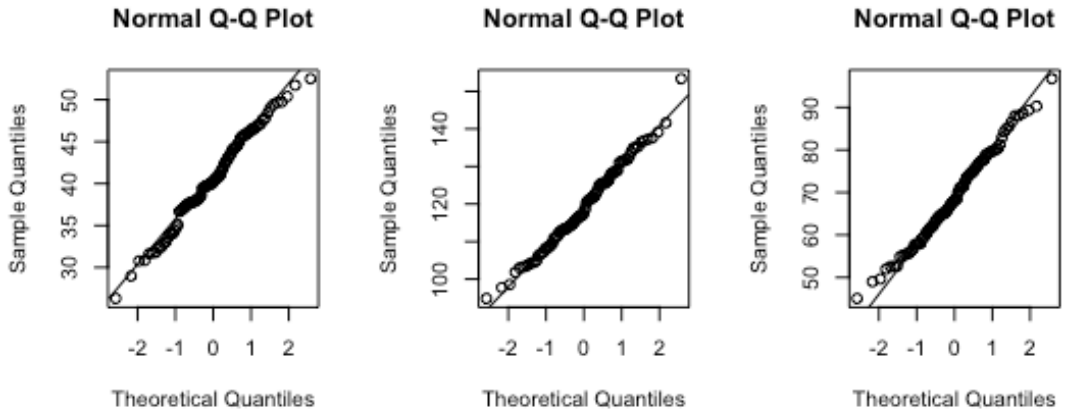
- Bell shaped curve
- Symmetrical
- Unimodal






```
# Checking distribution

## Visually
par(mfrow= c(2,3))
hist(Age)
hist(SBP)
hist(DBP)

qqnorm(Age)
qqline(Age)

qqnorm(SBP)
qqline(SBP)

qqnorm(DBP)
qqline(DBP)
```






```
# Showing Normal curve

hist(Age, ylim=c(0,.08), probability = TRUE)
curve(dnorm(x, mean=mean(Age), sd=sd(Age)), add=TRUE)

hist(SBP, ylim=c(0,0.04), probability = TRUE)
curve(dnorm(x, mean=mean(SBP), sd=sd(SBP)), add=TRUE)

hist(DBP, ylim=c(0,0.04), probability = TRUE)
curve(dnorm(x, mean=mean(DBP), sd=sd(DBP)), add=TRUE)

# Q-Q Plot

qqnorm(Age)
qqline(Age)

qqnorm(SBP)
qqline(SBP)

qqnorm(DBP)
qqline(DBP)
```

Characteristics of normal distribution

1. Shape of the curve – smooth symmetrical bell-shaped
2. Mean=Median
3. Skewness ~ 0 (usually ±2)
4. Kurtosis ~ 0 (usually ±2)

```
> library(psych)
> describe(Age)
   vars   n  mean   sd median trimmed  mad   min  max range  skew kurtosis   se
X1    1 100 40.62 5.44  40.18    40.7 5.18 26.31 52.5  26.2 -0.12    -0.47 0.54
> describe(SBP)
   vars   n   mean sd median trimmed   mad   min    max range skew kurtosis  se
X1    1 100 119.32 11 117.81  119.12 11.49 94.85 153.37 58.52 0.24    -0.23 1.1
> describe(DBP)
   vars   n  mean   sd median trimmed  mad   min   max range skew kurtosis   se
X1    1 100 69.09 10.7  68.12   68.84 11.7 45.07 96.75 51.68 0.15    -0.58 1.07
```

Test of Normality

- Anderson–Darling Test
- Corrected Kolmogorov–Smirnov Test (Lilliefors Test)
- Cramér–von-Mises Criterion
- D'agostino's K-squared Test
- Jarque–Bera Test
- Pearson's Chi-square Test
- Shapiro–Francia
- Shapiro–Wilk Test

```
> # Normality test
>
> shapiro.test(Age)

        Shapiro-Wilk normality test

data:  Age
W = 0.98956, p-value = 0.6295

> shapiro.test(SBP)

        Shapiro-Wilk normality test

data:  SBP
W = 0.98957, p-value = 0.6297

> shapiro.test(DBP)

        Shapiro-Wilk normality test

data:  DBP
W = 0.99029, p-value = 0.688
```

Use Normality test with caution

- Small samples almost always pass a normality test. *Normality tests have little power to tell whether or not a small sample of data comes from a Gaussian distribution.*
- With large samples, minor deviations from normality may be flagged as statistically significant, *even though small deviations from a normal distribution won't affect the results of a t test or ANOVA.*

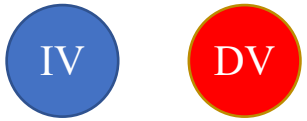
What would you do if the distribution is not normal?

1. Validate data entry
2. Transform the data
3. Use non-parametric test

Statistical analysis

Descriptive

Univariable

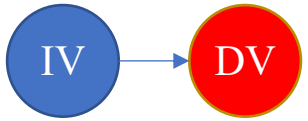


e.g., Describe socio-demographic characteristics - Age, Sex, Race etc.

e.g., Prevalence of hypertension.

Analytical

Bivariable



e.g., Compare demographic characteristics between two population – Compare age between male & female

e.g., Distribution of gender by hypertension status

Multivariable

e.g., How demographic characteristics (more than one factors) explain hypertension

Analytical tests able to

1. Determine **presence of difference** (or similarity)
2. Determine **degree of difference**
3. Determine the **direction of changes (trend)**
4. **Predict changes** (outcomes)

Is there any difference between A & B?

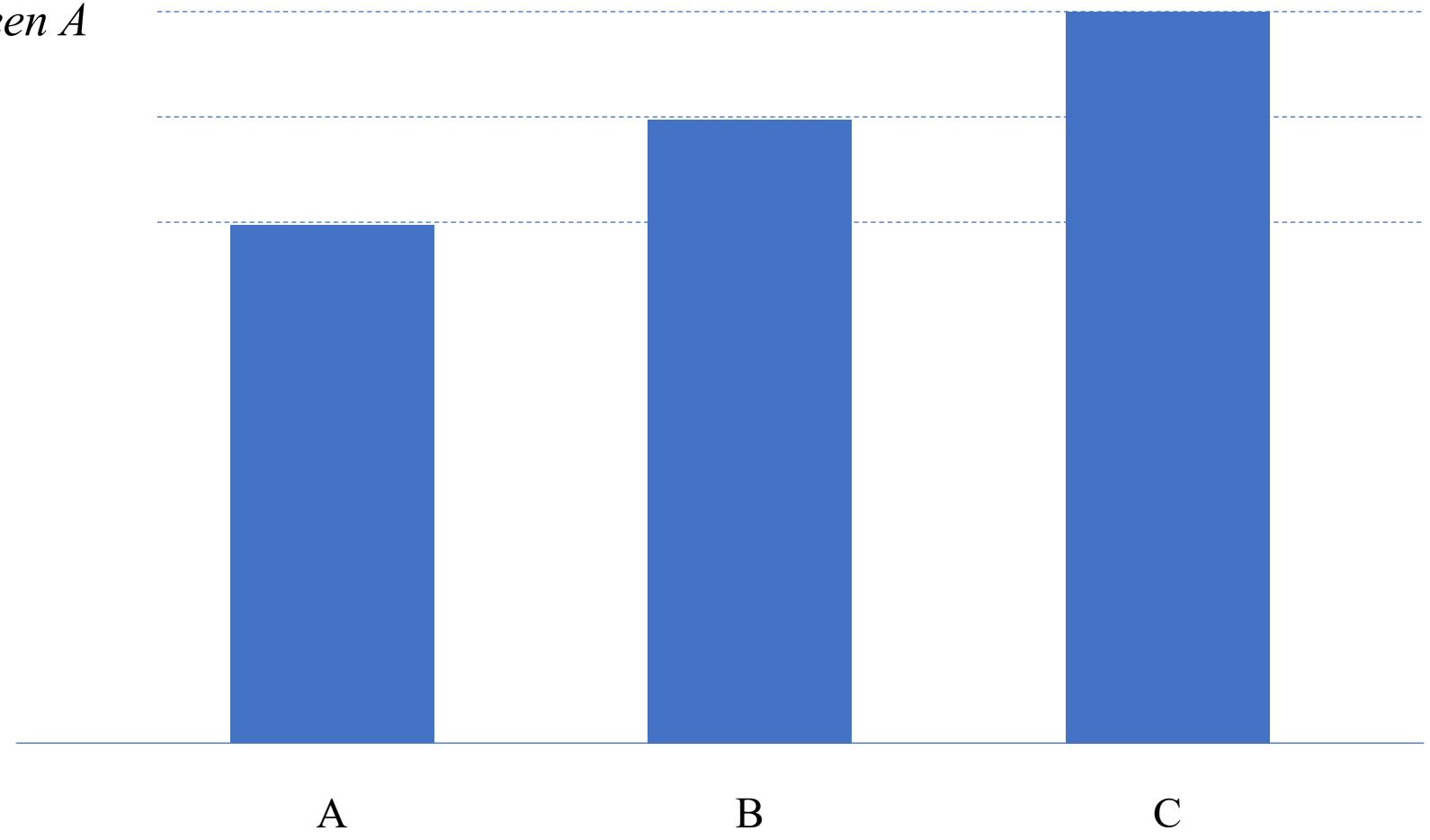
Which one is taller? A or B?

How big is the difference between A & B?

Is C different from A & B?

Is there any pattern now?

If there will be D, can you predict how tall is D?



Descriptive statistics

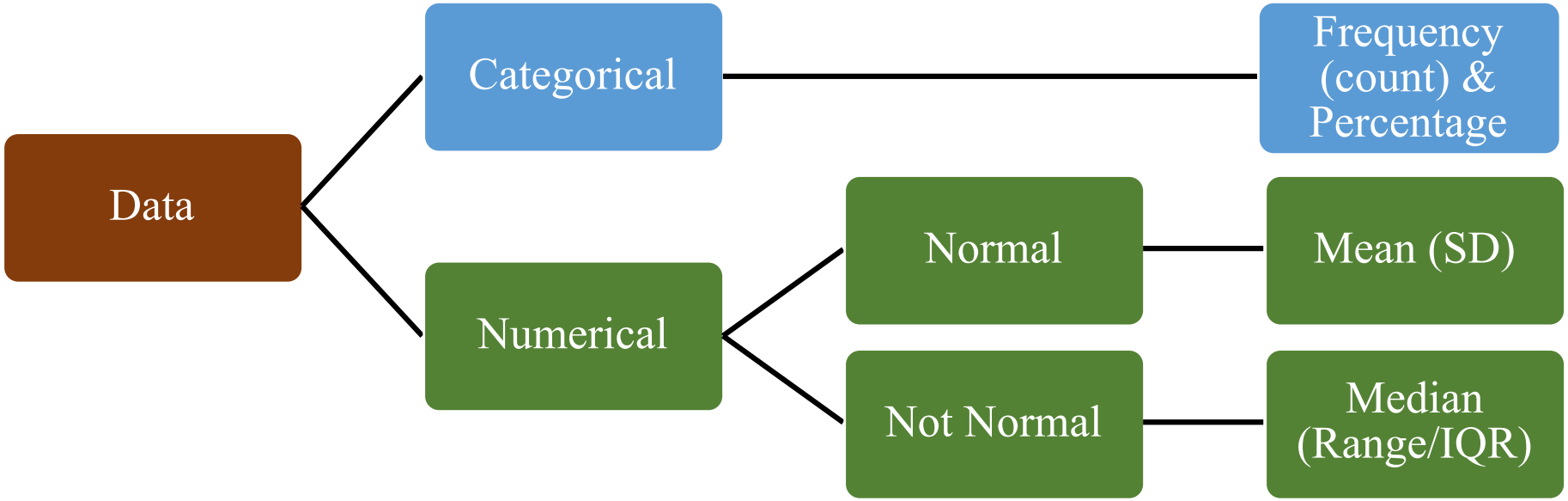
Basic Biostatistics

Jamalludin Ab Rahman

Descriptive Statistics

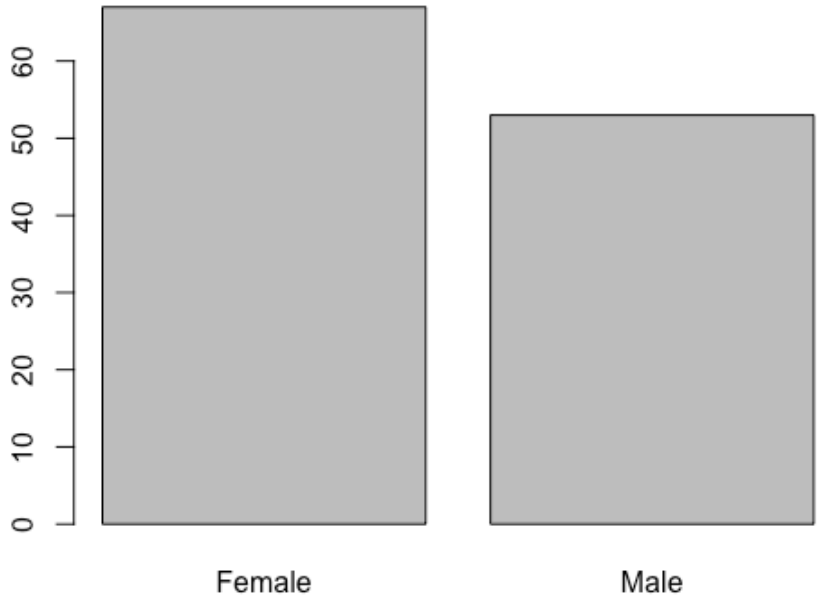
- Explain **one variable** at one time
- Method based on level of measurement
  - Categorical
    Frequency (Percentage)
  - Numerical
    Central measures (e.g. mean, median) & Dispersion (e.g. variance, standard deviation, range, min-max, interquartile range)

How to describe a data



Describe categorical variable

```
> # Describe categorical variable
> table(Sex)
Sex
Female   Male
    67     53
> round(prop.table(table(Sex))*100,
digit=1)
Sex
Female   Male
  55.8   44.2
>
> par(mfrow= c(1,1))
> plot(Sex)
```



Describe numerical variable

```
> # Describe numerical variables (Age, SBP & DBP)
> library(psych)
> describe(Age)
   vars   n  mean   sd median trimmed  mad  min   max range skew kurtosis   se
X1    1 120 40.01 4.48  40.02   39.94 4.35 29.9 52.43 22.53 0.19    -0.15 0.41
> describe(SBP)
   vars   n   mean   sd median trimmed  mad   min    max range  skew kurtosis   se
X1    1 120 119.93 9.21 120.19  119.95 9.34 98.47 142.03 43.56 -0.02    -0.44 0.84
> describe(DBP)
   vars   n  mean    sd median trimmed   mad   min    max range  skew kurtosis   se
X1    1 120 70.54 10.72  70.97   70.91 10.55 44.83 100.84 56.01 -0.16     0.05 0.98
```

“Table 1”

```
# Using gtsummary to describe all variables
library(gtsummary)
library(tidyverse)

detach(data2)
data2 %>%
  tbl_summary(
    statistic = all_continuous() ~ c("{mean} ({sd}),
                                     {median} ({p25}, {p75}),
                                    {min} - {max}"),
    digits = all_continuous() ~ 1
  )
```

Characteristic	N = 120[1]
ID	60.5 (34.8), 60.5 (30.8, 90.2), 1.0 - 120.0
Age	40.0 (4.5), 40.0 (37.1, 43.0), 29.9 - 52.4
Sex	
Female	67 (56%)
Male	53 (44%)
SBP	119.9 (9.2), 120.2 (113.3, 125.7), 98.5 - 142.0
DBP	70.5 (10.7), 71.0 (63.9, 77.9), 44.8 - 100.8

[1] Statistics presented: Mean (SD), Median (IQR), Range; n (%)

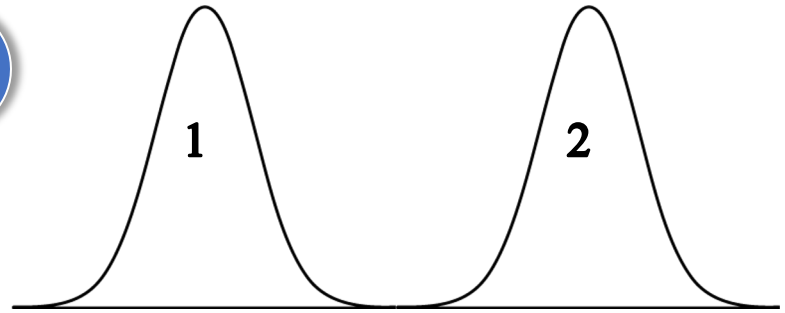
Analytical statistics

Basic Biostatistics

Jamalludin Ab Rahman

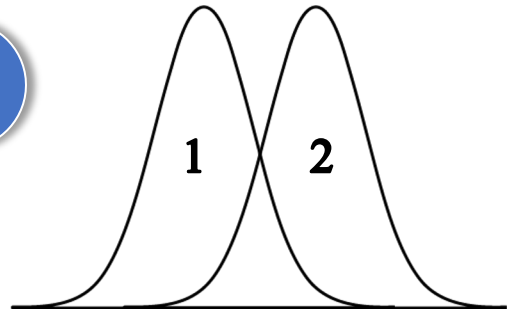
Comparing difference

A

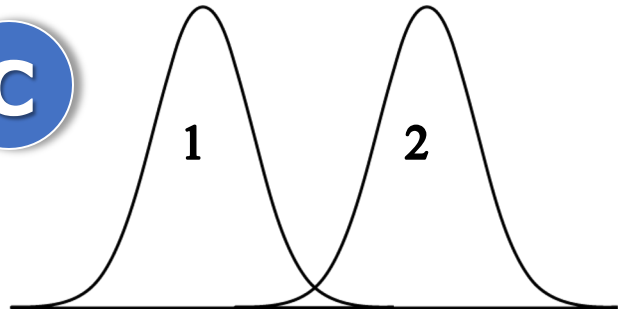


Which of the following shows true difference between two populations?

B



C



3 statistics to compare values

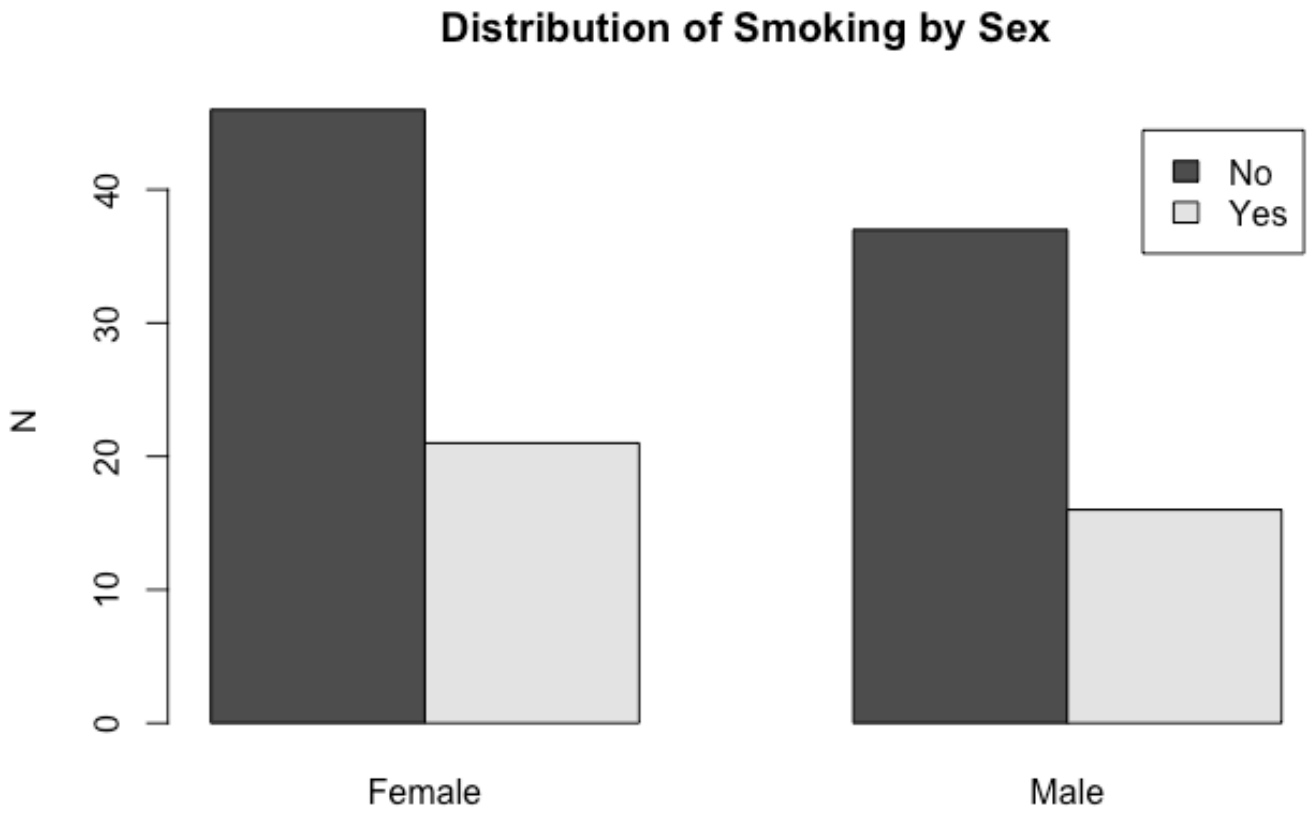
1. P-value
2. Confidence interval
3. Effect size

P value

- P-value is ‘likely’ or ‘unlikely’ that H_o is true
- Taking 0.05 as the cut-off point (α), if $P \leq 0.05$, it is then ‘unlikely’ H_o is true, therefore reject H_o

Hypothesis Testing using bivariable analysis

- Try to prove that there is relationship between Smoking and Sex
- H_o: No difference in proportion of smoking between male and female

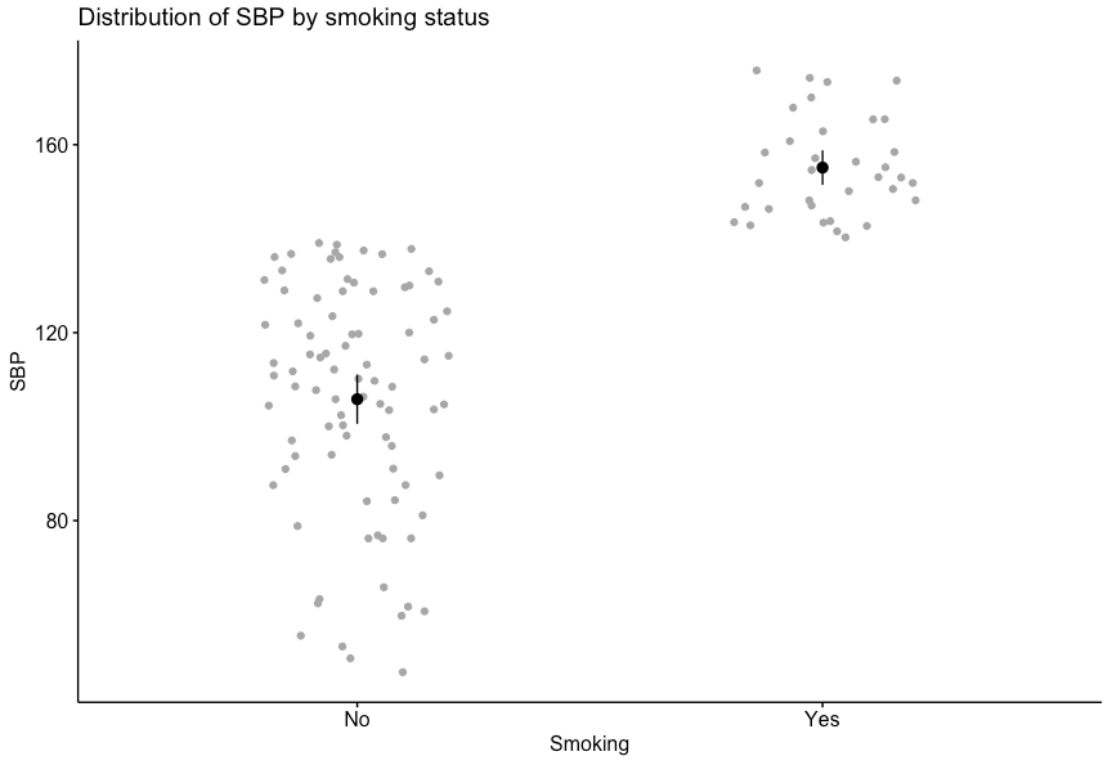



```
> # Cross-tabulate Sex with Smoking
> x <- table(Smoking, Sex)
> barplot(x, ylab="N",
+         beside = TRUE,
+         legend.text = TRUE,
+         main = "Distribution of Smoking by Sex")
> ftable(x)
        Sex Female Male
Smoking
No                46   37
Yes               21   16
> round(prop.table(x)*100, digit=1)
       Sex
Smoking Female Male
    No    38.3 30.8
    Yes   17.5 13.3
> chisq.test(x)

       Pearson's Chi-squared test with Yates'
continuity correction
```

Confidence Interval

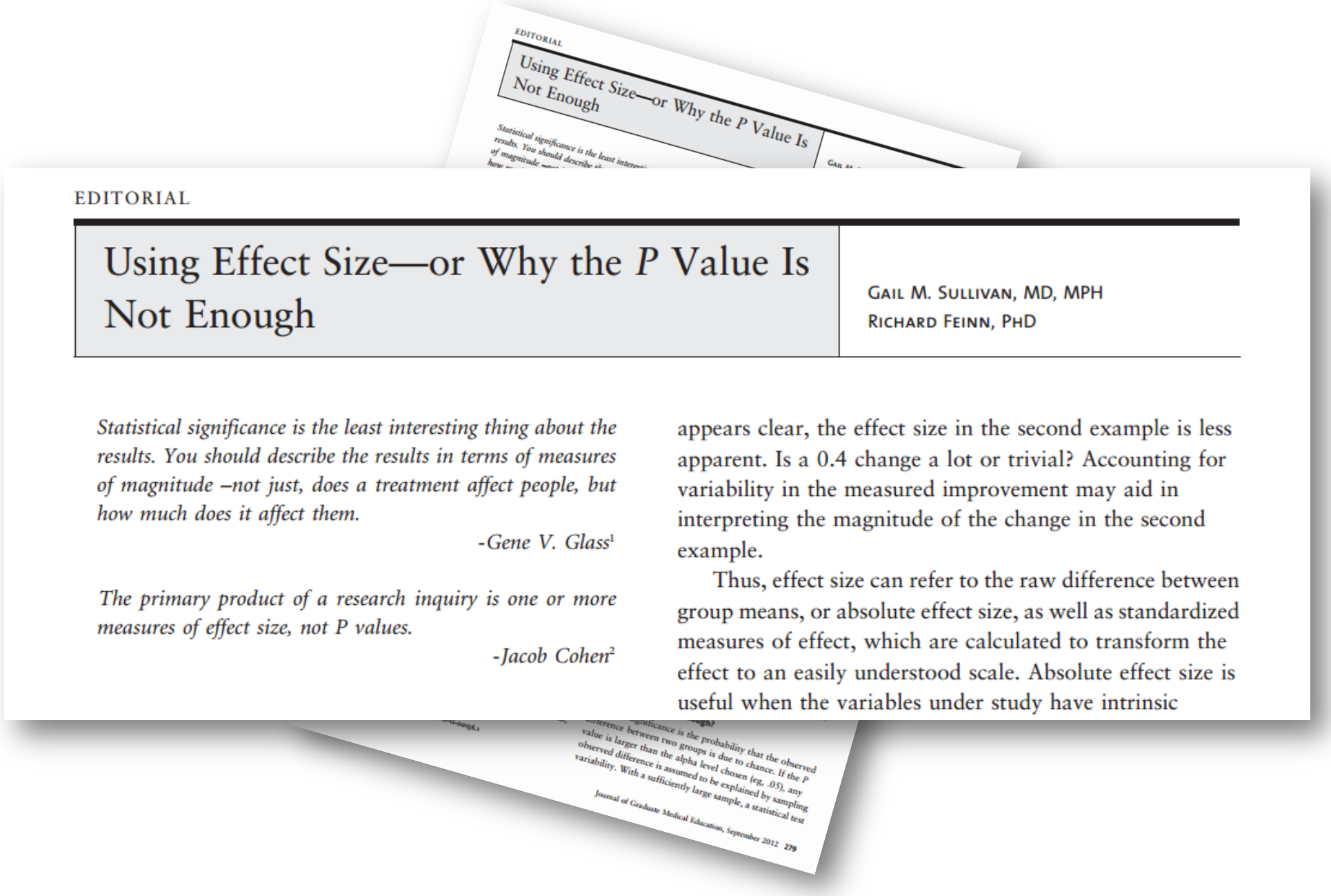
- Range of plausible values
- Narrow interval → high precision
  Wide interval → poor precision
- How narrow is narrow? And how wide is wide? Base on your clinical judgment

```
> # Error bars
> library(tidyverse)
> library(ggpubr)
>
> ggerrorplot(data=data3, x="Smoking",
y="SBP", main = "Distribution of SBP by
smoking status",
+             desc_stat = "mean_ci",
+             add = "jitter",
+             add.params = list(color =
"darkgray"))
>
> t.test(SBP~Smoking)

        Welch Two Sample t-test

data:  SBP by Smoking
t = -15.392, df = 117.07, p-value < 2.2e-16
alternative hypothesis: true difference in
means is not equal to 0
95 percent confidence interval:
 -55.64642 -42.95939
sample estimates:
 mean in group No mean in group Yes
         105.8336          155.1365
```



Effect size

- The measure of effect irrespective of sample size
- Cohen (1988) classify effect size into
  - Low (<0.3)
  - Medium (0.3-0.7)
  - Large (> 0.7)
- Manual calculation or web based calculation



EDITORIAL

Using Effect Size—or Why the *P* Value Is Not Enough

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Statistical significance is the least interesting thing about the results. You should describe the results in terms of measures of magnitude –not just, does a treatment affect people, but how much does it affect them.

-Gene V. Glass[1]

The primary product of a research inquiry is one or more measures of effect size, not P values.

-Jacob Cohen[2]

appears clear, the effect size in the second example is less apparent. Is a 0.4 change a lot or trivial? Accounting for variability in the measured improvement may aid in interpreting the magnitude of the change in the second example.

Thus, effect size can refer to the raw difference between group means, or absolute effect size, as well as standardized measures of effect, which are calculated to transform the effect to an easily understood scale. Absolute effect size is useful when the variables under study have intrinsic

```
> # Effect size
> library(effectsize)
>
> model <- aov(SBP ~ Smoking, data=data3)
> omega_squared(model)
For one-way between subjects designs, partial omega squared is
equvilant to omega squared.
Returning omega squared.
Parameter | Omega2 |       90% CI
--------------------------------
Smoking   |   0.51 | [0.41, 0.60]
> interpret_omega_squared(0.51, rules = "field2013")
[1] "large"
(Rules: field2013)
```

What test to use?

Variable 1	Variable 2	Test
Categorical	Categorical	Chi-square
Categorical (2 pop)	Numerical (Normal)	Independent sample t-test
Categorical (2 pop)	Numerical (Not Normal)	Mann-Whitney U test
Categorical (> 2 pop)	Numerical (Normal)	One-way ANOVA
Categorical (> 2 pop)	Numerical (Not Normal)	Kruskal-Wallis test
Numerical (Normal)	Numerical (Normal)	Pearson Correlation Coefficient Test
Numerical (Normal/ Not Normal)	Numerical (Not Normal)	Spearman Correlation Coefficient Test
Numerical (Normal)	Numerical (Normal) – Paired	Paired t-test
Numerical (Not Normal)	Numerical (Not Normal) – Paired	Wilcoxon Signed Rank Test

Summary

1. Identify & define variables
2. Type – independent vs. dependent
3. Level of measurements – nominal, ordinal or continuous
4. Check distribution – Normal vs. Not Normal
5. Decide what to do - descriptive vs. analytical